



Identifying the key impact factors of carbon emission in China: Results from a largely expanded pool of potential impact factors

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ABSTRACT

Carbon emission reduction (CER) comes to be the principle in most countries particularly China, the largest carbon emitter. For finding an efficient solution, the priority is to find the key impact factors (KIFs) of carbon emission. Previous studies for identifying KIFs, which partially selected only a few potential impact factors (PIFs), are inconsistent in their findings. This study aims to explore the KIFs of carbon emission in China among 43 PIFs, which comprehensively covers 30 relevant studies. The KIFs in China are identified using the Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) model with correlation analysis, partial correlation analysis and stepwise regression. The findings of this study are as follows: (1) China's carbon emission has five KIFs: the real GDP per capita, urbanization rate, ratio of tertiary to secondary industry, ratio of renewable energy, and fixed assets investment; (2) the most significant carbon emission contributor is real GDP per capita and the most significant carbon emission inhibitor is urbanization rate. This study provides the reliable KIFs for governors' targeted decision-making on CER, and policy implications from the identified KIFs are highlighted.

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1. Introduction

Carbon emission has been recognized as the main cause of climate change leading to various risks and economic loss (Shi et al., 2017). The total amount of carbon emission at the global level has increased approximately triple, i.e. from 9385.8 million tons in 1960 to 35,848.6 million tons in 2013, showing an annual increasing rate of 2.8% (World Bank, 2017). As reported by the United Nation Office for Disaster Risk Reduction, the average land surface temperature increased by 0.85 °C from 1880 to 2012, which has led to substantial species extinction and global food supply and demand imbalance (New York Times, 2015). Human-beings are suffering from the extreme weather, which has led to over 600,000 people died and 4.1 billion people wounded, as well as economic loss of over 1.9 trillion dollars in the past two decades (New York

Times, 2015). A warning from Stern (2007) stated that there would be a loss of 5% annual global GDP to balance out the overall costs and risks from global warming if no action was taken to reduce carbon emission. Therefore, it is considered imperative to conduct the CER from a global perspective (Shuai et al., 2017a).

China, as the largest emitter in the world, has taken up more than a quarter of the global carbon emission (Ma et al., 2017a). Meanwhile, the industrialization in China, which is considered as the major contributor of carbon emission, will continue to play the role in the following decades (Chen et al., 2017). Such status quo has aroused global attention to the carbon emission of China, who is facing the great pressure and challenges for CER (Shen et al., 2018). To do that efficiently, there is a strong science consensus that it is significant to identify the KIFs of carbon emission, which may directly influence the constitution of the CER measures, policies and strategies (Fan et al., 2006).

The topic of studying KIFs on carbon emission has attracted much attention from researchers (Shuai et al., 2017b). The impact factors in previous studies can be classified into population, affluence and technology (Ma et al., 2017b). In those studies, a category of impact factors of carbon emission may have different proxies. For

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Nomenclature list

Abbreviation

CER	carbon emission reduction
GDP	gross domestic product
IPAT	Impact = Population × Affluence × Technology
KIF	key impact factor
PIF	potential impact factor
STIRPAT	Stochastic Impacts by Regression on Population, Affluence, and Technology

example, “urbanization rate” was used as the proxy of population in Zheng et al. (2016), while Fu et al. (2015) adopted “total population” and Zoundi (2016) selected “population growth rate”. One problem is that each of the three proxies can only partially stand for the population. The other problem is that researchers selected only several factors that could be tested with their available data as the PIFs. The incomprehensiveness of PIFs directly leads to the inaccurate identification of KIFs, i.e., previous studies ignored the factors that might become the KIFs when selecting PIFs. For addressing the two problems, this study aims to identify more reliable KIFs of carbon emission in China based on a largely expanded pool of PIFs for tailoring CER strategies.

This study is innovative owing to the following two aspects. First, previous studies selected limited amount of factors (usually less than seven), while this study systematically selected the 43 PIFs by reviewing the previous studies that explore the KIFs in different countries or regions, which enables the results with more reasonableness. Second, this study is also innovative in the research methodology, as this is the first study to eliminate the partial correlation between multiple PIFs, which makes the results more reliable. The contributions of this research are from the theoretical and practical aspects. Theoretically, this study provides a more integrated and accurate group of KIFs of carbon emission. The methodology can serve as a guidance for scientifically selecting KIFs. Besides, this comprehensive concept can be extended to other countries as well as to other pollutants such as sulfur, haze and waste water. Practically, the identified KIFs in this study are valuable reference for the governments to tailor policies for effective CER.

2. Literature review

2.1. Methods for identifying the KIFs of carbon emission

There are various methods for identifying the KIFs, such as interpretive structural modeling (Samantra et al., 2016), social network analysis (Webster et al., 2016) and structural equation model (Xiong et al., 2014). However, these methods were critiqued relatively subjective, since the data used in these methods are from questionnaire surveys rather than the second-hand data (Shen et al., 2016). The samples of carbon emission are actual second-hand data, which indicates these methods are inappropriate for identifying KIFs on carbon emission in this study.

The current methods for exploring the KIFs of carbon emission can be classified into two categories, namely Kaya identity and STIRPAT (Wu et al., 2016). Wu et al. (2016) employed the Kaya identity with Monte Carlo simulation to examine the KIFs of carbon emission in China. Sumabat et al. (2016) applied the re-write Kaya identity to analyze factors that influence carbon emissions due to

fossil energy consumption in China to explore key factors for policies promoting CER. Nian et al. (2014) combined the Kaya identity and the decomposition technique to identify KIFs of carbon emission from nuclear power generation. Similarly, Shahiduzzaman and Layton (2015) decomposed the Kaya identity into population, GDP per capita, energy intensity and carbon intensity to examine the KIFs in the United States. Conventionally, using the Kaya identity, carbon emission is decomposed into limited factors as the decomposed factors needed to be explained logically and possess the real meaning. However, STIRPAT, derived from IPAT model, describes environmental impact (I) as a function of population (P), affluence (A) and technology (T) with stochastic status, and each function can be represented into different factors. As STIRPAT model can be expanded to incorporate unlimited additional factors, this method became a well-known technique that was widely adopted to identify the KIFs of carbon emissions. For example, Wang et al. (2017) selected eight PIFs of carbon emission using STIRPAT model for examining the KIFs in Xinjiang, China. Employing STIRPAT model with panel data analysis, the research by Poumanyong and Kaneko (2010) identified the critical KIFs of carbon emission in 99 countries from eight nominated factors. This method is thus adopted to explore KIFs of carbon emission based on the PIFs in this study.

2.2. PIFs of carbon emission

Studies that examined the KIFs of the carbon emission select different PIFs. The PIFs are reviewed and listed in Table 1.

It can be easily shown from Table 1 that different researchers select different PIFs in their studies to identify KIFs. For example, Wang et al. (2012) selected factors including urbanization rate, GDP per capita, the share of the industry output value over the total GDP, and the share of the tertiary industry output value over the total GDP as the PIFs to explore the KIFs of carbon emission in Beijing, China. Li et al. (2015) examined the KIFs of carbon emission in Tianjin city on the basis of factors such as foreign direct investment, total permanent population, and energy use per GDP; Wang et al. (2017) used factors including total population, total fixed assets investment, percentage of gross import and export value to GDP and percentage of coal consumption to total energy consumption for studying Xinjiang, China; Zoundi (2016) adopted renewable energy consumption per capita population growth and GDP per capita as the PIFs to examine the KIFs in 25 African countries; and the PIFs adopted in de Alegría et al. (2016) are renewable energy consumption share as a proportion of total Primary Consumption, total population and energy intensity; and Ohlan (2015) analyzed the KIFs of carbon emission in India using the factors including energy consumption per capita, GDP per capita, population density and the total exports and imports.

The inconsistency of using potential factors for one category not only happens for different regions, but also happens between the researches on identifying the KIFs in the same region. For identifying KIFs in China, Zhou and Liu (2016) used factors such as the share of the working-age population (16–64 years old), average household size, and GDP per capita as the PIFs; Xu and Lin (2017) used the total energy use divided by GDP, industry's coal consumption by its total energy consumption and urbanization rate as the PIFs; Xu et al. (2016) used GDP per unit energy consumption, total population and the ratio of industry sector value added in GDP as the PIFs; and Guan et al. (2017) adopted farmers annual net income per capita, population density, urban employment and the ratio of tertiary industry sector value added in GDP as the PIFs. The inconsistency of selecting PIFs definitely leads to the differences of the identified KIFs between their studies, which could partially guide the CER. Therefore, it is important to enlarge the pool of PIFs

Table 1
Summary of the literature on PIFs of carbon emission.

He et al. (2017)	29 provinces in China	<ul style="list-style-type: none"> • real GDP per capita • total population • urbanization rate • total energy use divided by GDP • the ratio of industry sector value added in GDP • the annual number of patents
Xu and Lin (2017)	Industry in China	<ul style="list-style-type: none"> • real GDP per capita • industry's coal consumption by its total energy consumption • urbanization rate • the ratio of industry sector value added in GDP • total population • total energy use divided by GDP
Zoundi (2016)	25 African countries	<ul style="list-style-type: none"> • real GDP per capita • energy consumption per capita • renewable energy consumption per capita • population growth
Wang et al. (2012)	Beijing city, China	<ul style="list-style-type: none"> • real GDP per capita • urbanization rate • the share of the industry sector output value over the total GDP • the share of the tertiary industry output value over the total GDP • total energy use divided by GDP • the annual number of patents
Zhang and Xu (2017)	30 provinces in China	<ul style="list-style-type: none"> • the total urban population • the share of the tertiary • industry output value over the total GDP • the ratio of land transfer revenue devoted to local public budgetary revenue • annual growth rate of construction land • real GDP per capita
Wang et al. (2017)	Xinjiang province, China	<ul style="list-style-type: none"> • real GDP per capita • total population • urbanization rate • the proportion of the secondary industry output value over the total GDP • the proportion of the tertiary industry output value over the total GDP • total fixed assets investment • percentage of gross import and export value to GDP • percentage of coal consumption to total energy consumption
Li et al. (2012)	China	<ul style="list-style-type: none"> • real GDP per capita • the share of the secondary industry output value over the total GDP • total population • urbanization rate • total energy use divided by GDP
Fu et al. (2015)	Wenzhou city, China	<ul style="list-style-type: none"> • real GDP per capita • total population • the share of the tertiary industry output value over the total GDP • industry energy consumption per unit of GDP • the share of the secondary industry output value over the total GDP • total energy consumption • total carbon emission divided by total energy consumption • urbanization rate • the share of the industry sector output value over the total GDP • the share of the service sector output value over the total GDP • total energy use divided by GDP • total population • real GDP per capita
Poumanyong and Kaneko (2010)	99 countries	<ul style="list-style-type: none"> • real GDP per capita • total population • urbanization rate • the ratio of actual amount of FDI in GDP • the ratio of the tertiary industry value to the secondary industry output value • GDP per energy consumption • real GDP per capita • total resident population • energy intensity • urbanization rate • real GDP per capita • urbanization rate • share of secondary industry in GDP • share of coal consumption in energy consumption • real GDP per capita • total population • the ratio of industry sector value added in GDP • energy consumption per unit of value added by industry • fossil fuel intensity of total final energy consumption • total CO2 emissions per unit of energy consumed • real GDP per capita population density • the added values of secondary and tertiary industry in the GDP
Zhang and Zhou (2016)	China	<ul style="list-style-type: none"> • real GDP per capita • total population • urbanization rate • the ratio of actual amount of FDI in GDP • the ratio of the tertiary industry value to the secondary industry output value • GDP per energy consumption • real GDP per capita • total resident population • energy intensity • urbanization rate • real GDP per capita • urbanization rate • share of secondary industry in GDP • share of coal consumption in energy consumption • real GDP per capita • total population • the ratio of industry sector value added in GDP • energy consumption per unit of value added by industry • fossil fuel intensity of total final energy consumption • total CO2 emissions per unit of energy consumed • real GDP per capita population density • the added values of secondary and tertiary industry in the GDP
Wang et al. (2011)	Shanghai city, China	<ul style="list-style-type: none"> • real GDP per capita • total resident population • energy intensity • urbanization rate • real GDP per capita • urbanization rate • share of secondary industry in GDP • share of coal consumption in energy consumption • real GDP per capita • total population • the ratio of industry sector value added in GDP • energy consumption per unit of value added by industry • fossil fuel intensity of total final energy consumption • total CO2 emissions per unit of energy consumed • real GDP per capita population density • the added values of secondary and tertiary industry in the GDP
Zheng et al. (2016)	73 cities in China	<ul style="list-style-type: none"> • real GDP per capita • urbanization rate • share of secondary industry in GDP • share of coal consumption in energy consumption • real GDP per capita • total population • the ratio of industry sector value added in GDP • energy consumption per unit of value added by industry • fossil fuel intensity of total final energy consumption • total CO2 emissions per unit of energy consumed • real GDP per capita population density • the added values of secondary and tertiary industry in the GDP
Brizga et al. (2013)	15 countries	<ul style="list-style-type: none"> • real GDP per capita • total population • the ratio of industry sector value added in GDP • energy consumption per unit of value added by industry • fossil fuel intensity of total final energy consumption • total CO2 emissions per unit of energy consumed • real GDP per capita population density • the added values of secondary and tertiary industry in the GDP
Liu, 2015	China	<ul style="list-style-type: none"> • real GDP per capita • total population • the ratio of industry sector value added in GDP • energy consumption per unit of value added by industry • fossil fuel intensity of total final energy consumption • total CO2 emissions per unit of energy consumed • real GDP per capita population density • the added values of secondary and tertiary industry in the GDP

Table 1 (continued)

Martínez-Zarzoso and Maruotti, 2011	developing countries	<ul style="list-style-type: none"> • industry energy use per unit GDP • energy consumption per capita • real GDP per capita • the share of the secondary industry output value over the total GDP • total population • urbanization rate
Lin et al. (2016)	African countries	<ul style="list-style-type: none"> • real GDP per capita • population growth rate • growth rate of industrial and agricultural value-added as a percentage of GDP • proportion of fossil fuel in total energy consumption per GDP
Zhang and Lin (2012)	China	<ul style="list-style-type: none"> • real GDP per capita • total population • urbanization rate • the ratio of industry sector value added in GDP • the ratio of service sector value added in GDP • total energy consumption • total energy use divided by GDP • emission from fuel consumption • total CO2 emissions divided by total energy use
Yao et al. (2015)	G20 countries	<ul style="list-style-type: none"> • real GDP per capita • total population • the ratio of industry sector value added in GDP • energy intensity
Guan et al. (2017)	China	<ul style="list-style-type: none"> • carbon emission per energy consumption • real GDP per capita • urban employment • the ratio of secondary industry sector value added in GDP • the ratio of secondary industry sector value added in GDP • the farmers annual net income per capita
Zhou and Liu (2016)	China	<ul style="list-style-type: none"> • population density • real GDP per capita • total population • urbanization rate • the share of the working-age population (16–64 years old) • the average household size
Li et al. (2011)	China	<ul style="list-style-type: none"> • industry energy use per unit industrial added value • real GDP per capita • the share of the secondary industry output value over the total GDP • total population • urbanization rate • the economic output of per unit energy consumption
Wang et al. (2013)	Guandong province, China	<ul style="list-style-type: none"> • fossil fuel consumption • real GDP per capita • carbon emission per GDP • the share of the secondary industry output value over the total GDP • the share of the secondary industry output value over the total GDP • the ratio of total imports and exports value to GDP • the ratio of fossil fuel in total energy consumption
Xu et al. (2017)	China	<ul style="list-style-type: none"> • real GDP per capita • urbanization rate • the proportion of the secondary industry output value over the total GDP • the proportion of the tertiary industry output value over the total GDP • energy consumption per unit of value added by industry
de Alegría et al. (2016)	Spain	<ul style="list-style-type: none"> • real GDP per capita • total population • renewable energy consumption share as a proportion of total energy use • total energy use divided by GDP
Ohlan (2015)	India	<ul style="list-style-type: none"> • real GDP per capita • energy consumption per capita • population density • the total exports and imports
Kang et al. (2016)	China	<ul style="list-style-type: none"> • real GDP per capita • total population • total energy use divided by GDP • urbanization rate • the proportion of the secondary industry output value over the total GDP
Xu et al. (2016)	China	<ul style="list-style-type: none"> • urbanization rate • real GDP per capita • urbanization rate • total population • GDP per unit energy consumption
Yang et al. (2015)	Beijing city, China	<ul style="list-style-type: none"> • the ratio of industry sector value added in GDP • the proportion of young population(15) • working age population (aged 15–64) • the share of aging population (aged 65 and older) • percentage of the floating population in the total population

(continued on next page)

Table 1 (continued)

Shuai et al. (2017b)	125 countries	<ul style="list-style-type: none"> • population divided by total number of households • energy consumption per capita • industry energy consumption divided by industry output • real GDP per capita • urban population • energy use per GDP
Fan et al. (2006)	208 countries	<ul style="list-style-type: none"> • real GDP per capita • total population • energy use per GDP • urbanization rate
Li et al. (2015)	Tianjing city	<ul style="list-style-type: none"> • ratio of population aged 15–64 over the total population • real GDP per capita • total permanent population • urbanization rate • total energy use divided by GDP • the share of the industry sector output value over the total GDP
Li et al. (2016)	China	<ul style="list-style-type: none"> • foreign direct investment • real GDP per capita • total population • carbon emission per GDP • urbanization rate • the share of the secondary industry output value over the total GDP • percentage of coal consumption to total energy consumption

by combining all of the PIFs in previous studies for identifying the KIFs of carbon emission that serve as references for CER with more confidence.

With this aim, the PIFs in this study are identified through a comprehensive literature review. For effective analysis, the factors in Table 1 are grouped into six commonly appreciated dimensions: population, urbanization, energy structure, energy intensity, industry structure and economy. There are some factors in Table 1 used for studying other countries rather than China, such as India, Spain or even 208 countries, they are also employed as the PIFs in this study for identifying the KIFs in China. In processing those factors, this study also gives a unified name for those factors with the same literal meaning for the convenience of data analysis. For example, “share of secondary industry in GDP” in Zheng et al. (2016) and “the proportion of the secondary industry output value over the total GDP” in Xu et al. (2017) have the same literal meaning, which are named as “the ratio of the secondary industry output value over the total GDP”. The PIFs of carbon emission in this research are shown in Table 2.

As discussed above, different researches select different and limited PIFs to identify the KIFs of carbon emission subjectively, which leads to results unreliable. There is a need to systematically summarize PIFs and identify the KIFs from the largely expanded pool of PIFs.

3. Research methods

3.1. STIRPAT model

STIRPAT is introduced for addressing the limitation of IPAT that only allows estimation on the proportionate impact of environmental change by changing one factor and simultaneously holding the others constant. Dietz (1994) developed the STIRPAT model to randomness parameters on IPAT, which is represented as follows:

$$I = aP^bA^cT^de \quad (1)$$

For the simplicity of calculation, Equation (1) can be rewritten in logarithmic form, as follows:

$$\ln I = \ln a + b \ln P + c \ln A + d \ln T + \ln e \quad (2)$$

where, I stands for the environment impact, which indicates carbon

emission in this research. In this form, a is the constant term, e is the error term. b , c and d can be seen as the elastic coefficient in economics, reflecting the sensitivity of the influence on $\ln I$ when changing P , A , and T , i.e., the larger value of the coefficient means the variable is more important.

As discussed above, the STIRPAT model allows other impact factors to be added in order to analyze their influence on environmental pressure (He et al., 2017). For comprehensively identifying the KIFs of carbon emission in China, the STIRPAT model is expanded referring to Table 2. The expanded theoretical STIRPAT model is represented as follows:

$$\begin{aligned} \ln I = & a_1 + a_2 \ln WP + a_3 \ln YP + a_4 \ln AP + a_5 \ln TP + a_6 \ln HS \\ & + a_7 \ln PD + a_8 \ln PR + a_9 \ln PG + a_{10} \ln UR + a_{11} \ln UP \\ & + a_{12} \ln CL + a_{13} \ln PP + a_{14} \ln FP + a_{15} \ln UE + a_{16} \ln CE \\ & + a_{17} \ln RE + a_{18} \ln FE + a_{19} \ln RC + a_{20} \ln IC + a_{21} \ln TC \\ & + a_{22} \ln TR + a_{23} \ln TF + a_{24} \ln CC + a_{25} \ln EG + a_{26} \ln EI \\ & + a_{27} \ln EC + a_{28} \ln TA + a_{29} \ln GC + a_{30} \ln SG + a_{31} \ln TG \\ & + a_{32} \ln IG + a_{33} \ln SS + a_{34} \ln GI + a_{35} \ln GA + a_{36} \ln TS \\ & + a_{37} \ln RG + a_{38} \ln IE + a_{39} \ln FA + a_{40} \ln FD + a_{41} \ln TI \\ & + a_{42} \ln FI + a_{43} \ln FG + a_{44} \ln DP + a_{45} \end{aligned} \quad (3)$$

As shown above, compared with traditional STIRPAT models, a large number of extra PIFs are incorporated in the STIRPAT model for examining the KIFs of carbon emission in this study. The next step is to calculate the coefficient of each PIF, thus regression analysis is adopted.

3.2. Stepwise regression analysis

The stepwise regression is a widely used method for multivariate linear regression and quick way to select best model from large mounts of candidate models. For example, the research by Bai et al. (2016) employed stepwise regression method to identify the key impact factors at the regional level in China. Zimin and Semenov (2005) analyzed the best-fitting parameters of each fuel cell factor by using stepwise regression. Similarly, in order to select the significant factors of solid waste reduction from various different factors, Franchetti (2011) applied stepwise regression to achieve this aim. Adding the one factor into the linear model will result in

Table 2
The PIFs of carbon emission.

Dimension	Factor	Abbreviation	Unit
Population	The ratio of population aged 15–64 over total population	WP	percent
	The ratio of population aged 0–14 over total population	YP	percent
	The ratio of population aged over 65 over total population	AP	percent
	Total population	TP	ten thousand person
	The average household size	HS	person
	Population density	PD	persons per square kilometer
	Population growth rate	PR	percent
Urbanization	Population growth	PG	persons
	Urbanization rate	UR	percent
	Urban population	UP	ten thousand persons
	Growth rate of construction land	CL	percent
	Total permanent population	PP	ten thousand persons
	The ratio of the floating population in total population	FP	percent
	Urban employment rate	UE	percent
Energy structure	The ratio of coal consumption in total energy consumption	CE	percent
	The ratio of renewable energy in total energy consumption	RE	percent
	The ratio of fossil fuel in total energy consumption	FE	percent
	Renewable energy consumption per capita	RC	kg of oil equivalent per person
	The ratio of industry's coal consumption in total energy consumption	IC	percent
	Total energy consumption	TC	kg of oil equivalent
	Total renewable energy consumption	TR	kg of oil equivalent
Energy intensity	Total fossil energy consumption	TF	kg of oil equivalent
	Carbon emission per energy consumption	CC	tons per kg of oil equivalent
	Energy consumption per GDP	EG	kg of oil equivalent per constant 1995 Yuan
	Energy consumption per industry's GDP	EI	kg of oil equivalent per constant 1995 Yuan
	Energy consumption per capita	EC	kg of oil equivalent per person
	Total patents	TA	item
	GDP per energy consumption	GC	constant 1995 Yuan per kg of oil equivalent
Industry structure	The ratio of the secondary industry output value over the total GDP	SG	percent
	The ratio of the tertiary industry output value over the total GDP	TG	percent
	The ratio of the industry sector output value over the total GDP	IG	percent
	The ratio of the service sector output value over the total GDP	SS	percent
	Growth rate of industrial value-added as a percentage of GDP	GI	percent
	Growth rate of agriculture value-added as a percentage of GDP	GA	percent
	The ratio of the tertiary industry output value to the secondary industry output value	TS	percent
Economy	Real GDP per capita	RG	constant 1995 Yuan
	The ratio of total imports and exports value to GDP	IE	percent
	Total fixed assets investment	FA	constant 1995 Yuan
	Total foreign direct investment	FD	constant 1995 Yuan
	The total exports and imports	TI	constant 1995 Yuan
	The farmers annual net income per capita	FI	constant 1995 Yuan per person
	The ratio of total foreign direct investment in GDP	FG	percent
	The ratio of land transfer revenue devoted to local public budgetary revenue	DP	percent

the rapid increase of calculation amount with the serious reduction of the accuracy of fitted values and significant p-value of each factor, which are the two basic criteria for selecting best model. As shown in Equation (3), there are totally 43 PIFs, thus theoretically, there are $2^{43}-1$ different kinds of regression models with the principle of permutation and combination theory. In order to quickly select best model from large amounts of candidate models, stepwise regression is applied in this study. In the main processing procedures, a factor may be selected by its significance in one step, then the colinearity will be checked through variance contribution to ensure that whether all the accepted independent variables are correlated with dependent variables. Meanwhile for the most part, another factor will be mandatorily excluded. When the number of the significant variables selected becomes stable, the algorithm stops the searching work and begins to tackle with the logging data with the established optimal fitting model (Gu et al., 2017).

3.3. Correlation analysis

Before regression analysis, it is considered important to examine whether correlations and multi-collinearity exist between dependent and independent factors (Chen and Lu, 2017). Previous researches Ayalew and Yamagishi (2005) showed that ensuring the correlation between each independent and dependent variables is

the precondition before performing regression analysis. This research thereby applied the Pearson's correlation coefficient, which is a widely used approach to examine the correlations between the variables (Choi, 2017).

The Pearson's correlation coefficient between two factors (x , y) is formulated as follows:

$$r_{xy} = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2} \sqrt{\sum_{i=1}^n (y_i - \bar{y})^2}} \quad (4)$$

where \bar{x} and \bar{y} present the average value of x and y respectively, and x_i and y_i denote the value of x and y of observation i respectively.

Partial correlation measures the degree of association between two random variables, with the effect of a set of controlling random variables removed. Partial correlation analysis is used to solve the multi-collinearity problem and to eliminate the spurious correlation (Fujita et al., 2015). Different from simple correlation analysis used for preliminary factor selection, partial correlation analysis is a method to test the correlation among preliminarily selected factors (Qiang et al., 2015). Therefore, partial correlation is applied in this study to examine the correlation between the PIFs with carbon emission. After the effect of factor z on x and y excluded, the partial correlation coefficient of factors x and y is formulated as follows:

$$\rho_{xy,z} = \frac{r_{xy} - r_{xz}r_{zy}}{\sqrt{1 - r_{xz}^2}\sqrt{1 - r_{zy}^2}} \quad (5)$$

where r_{ij} denotes the correlation coefficient between factors i and j ($i, j = x, y$ and z , and $i \neq j$).

4. Empirical analysis and results

As discussed above, this study identifies the KIFs of carbon emission in China through three steps, namely, correlation analysis, partial correlation analysis and stepwise regression. The data are collected from China Energy Statistical Yearbooks (1996–2015) covering the period from 1995 to 2014 on carbon emission and energy consumption (Statistics Database of Economic and Social Development of China (SDESDC), 2015). Total carbon emission is calculated with total energy consumption applying the algorithm adopted by Intergovernmental Panel on Climate Change (IPCC) (2006). The data on renewable energy consumption are from World Bank (2015), while the rest factors such as “Total foreign direct investment” and “Urban employment rate” are from the Statistics Database of Economic and Social Development of China (SDESDC) (2015). This study adopted statistics package SPSS 19.0 as the tool for correlation analysis, partial correlation analysis and stepwise regression.

4.1. The results of Pearson's correlation coefficient

In this study, Pearson's correlation coefficient is adopted for examining the correlation between dependent and each independent factor before conducting the stepwise regression. The results are shown in Table 3.

It can be seen from Table 3, carbon emission (I) is the dependent factor and other impact factors are the independent factors. Most of PIFs are significantly correlated with carbon emission. However, there are three factors including CL representing “Growth rate of construction land”, GI denoting “Growth rate of industrial value-added as a percentage of GDP” and GA “Growth rate of agriculture value-added as a percentage of GDP” shows no significant correlation with carbon emission. Therefore, CL , GI and GA are excluded in the partial correlation analysis. This study performs the correlation analysis using the other 40 PIFs, which have significant correlated with carbon emission.

Table 3
The Pearson's correlation coefficients between dependent and independent factors.

	WP	YP	AP	TP	HS	PD	PR	PG	UR
I	.902 ^a	-.941 ^a	.976 ^a	.927 ^a	-.930 ^a	.919 ^a	-.779 ^a	-.769 ^a	.957 ^a
	UP	CL	PP	FP	UE	CE	RE	FE	RC
I	.960 ^a	0.119	.927 ^a	.985 ^a	.960 ^a	-.725 ^a	-.941 ^a	.941 ^a	.942 ^a
	IC	TC	TR	TF	CC	EG	EI	EC	TA
I	-.836 ^a	.992 ^a	.952 ^a	.993 ^a	.685 ^a	-.808 ^a	-.780 ^a	.992 ^a	.955 ^a
	GC	SG	TG	IG	SS	GI	GA	TS	RG
I	.877 ^a	.524 ^b	.840 ^a	-.576 ^a	-.644 ^a	-0.358	-0.371	.795 ^a	.991 ^a
	IE	FA	FD	TI	FI	FG	DP		
I	.762 ^a	.969 ^a	.881 ^a	.994 ^a	.924 ^a	.711 ^a	.880 ^a		

^a Denotes the correlation is significant at the 0.01 level.

^b Denotes the correlation is significant at the 0.05 level.

4.2. The results of partial correlation analysis

After conducting the correlation analysis, the partial correlation analysis is applied to avoid the spurious correlation. Table 4 presents the results of calculating the partial correlation coefficients between the dependent and each independent factor.

Table 4 shows that 28 PIFs are not significantly correlated with carbon emission (I). There are 12 PIFs show partial correlation with carbon emission: TP , HS , PD , UR , PP , RE , TA , TS , RG , FA , FD and TI . The stepwise regression analysis is thus conducted on them. It is worthy to note that some key impact factors (KIFs) identified in others' research have been omitted. For example, factor “Energy consumption per GDP” and “the ratio of secondary industry” is commonly recognized as the KIFs in others' study (He et al., 2017). However, they are omitted in this research because of the low and insignificant partial correlation coefficient.

4.3. The results of stepwise regression analysis

After conducting the correlation and partial correlation analysis, there are 12 PIFs left for stepwise regression analysis, which indicates there theoretically exists $2^{12}-1=4095$ regression models. However, according to the fitting degree of the models to the data, this study selects eight candidate STIRPAT models with significant coefficients (at 0.05 level) of each factor, high R square and low standard error of estimate after stepwise regression selection. They are displayed in Table 5. Among them, Model 8 appears significant coefficients (at 0.05 level) for each factor, highest R square and lowest standard estimate error, which indicates Model 8 most fits the data. Ultimately, Model 8 is selected as the STIRPAT model.

5. Discussions

The coefficient of each factor in model 8 in the above section has presented the effect degree of the KIFs on the carbon emission in China. The results show that real GDP per capita is the largest contributor of carbon emission, followed by the urbanization considered as the largest inhibiting factor of carbon emission, and the ratio of tertiary to secondary industry, the ratio of renewable energy utilization, and the fixed assets investment. The implications of these findings will be discussed by analyzing the importance degree of each factor.

5.1. The real GDP per capita

This factor is the most frequently selected during the previous

Table 4

The partial correlation coefficients between dependent and each independent factor.

	WP	YP	AP	TP	HS	PD	PR	PG	UR
<i>I</i>	0.431	−0.315	0.531	.856 ^a	−.742 ^a	.642 ^b	−0.621	0.753	−.836 ^a
	UP	PP	FP	UE	CE	RE	FE	RC	IC
<i>I</i>	0.553	.692 ^a	0.696	0.104	−0.337	−.774 ^a	0.513	0.206	−0.316
	TC	TR	TF	CC	EG	EI	EC	TA	GC
<i>I</i>	0.441	0.056	0.481	0.521	−0.379	−0.223	0.647	0.659 ^a	0.541
	SG	TG	IG	SS	TS	RG	IE	FA	FD
<i>I</i>	0.159	0.351	−0.148	−0.321	−.725 ^a	.793 ^a	0.682	−.714 ^a	.669 ^a
	TI	FI	FG	DP					
<i>I</i>	.816 ^a	0.032	0.216	0.337					

^a Denotes the correlation is significant at the 0.01 level.^b Denotes the correlation is significant at the 0.05 level.**Table 5**

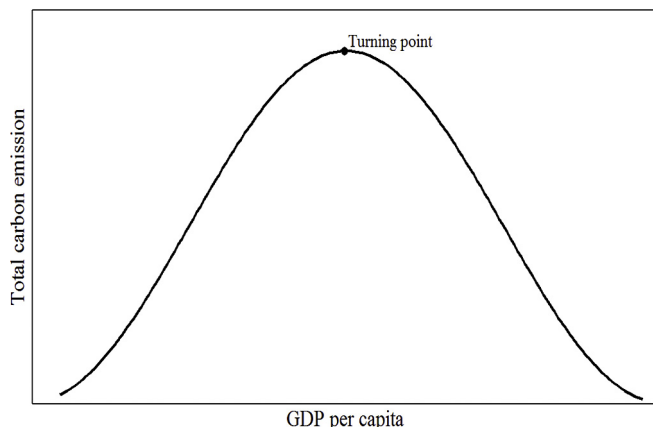
The STIRPAT models after stepwise regression selection.

Code	STIRPAT model	R square	Standard error of estimate
1	$\ln I = -1.738^a \ln RE + 12.939^a$	0.971	0.07591
2	$\ln I = -1.146^a \ln RE + 0.138^a \ln TA + 12.112^a$	0.985	0.05443
3	$\ln I = -1.213^a \ln RE + 0.261^a \ln TA - 0.82^a \ln UR + 9.762^a$	0.989	0.0471
4	$\ln I = -0.882^a \ln RE + 0.062^a \ln TA - 1.354^a \ln UR + 0.797^a \ln RG + 4.832^a$	0.993	0.03833
5	$\ln I = -0.826^a \ln RE - 1.37^a \ln UR + 0.966^a \ln RG + 4.095^a$	0.993	0.03786
6	$\ln I = -0.792^a \ln RE - 2.09^a \ln UR + 1.492^a \ln RG - 0.21^b \ln FA + 0.549$	0.995	0.03143
7	$\ln I = -1.778^a \ln UR + 2.112^a \ln RG - 0.338^a \ln FA - 1.059^a TS + 2.731^b$	0.996	0.02928
8	$\ln I = -0.342^b \ln RE - 1.735^a \ln UR + 1.84^a \ln RG - 0.286^a \ln FA - 0.654^b \ln TS - 1.203^b$	0.996	0.02818

^a Denotes the correlation is significant at the 0.01 level.^b Denotes the correlation is significant at the 0.05 level.

studies on carbon emission (see Table 1). However, there are two opinions in the main stream about its effect on carbon emission, i.e. it will increase the carbon emission (Wang et al., 2011), and the other appears an inverted U-shaped relationship known as carbon Kuznets curve (CKC) theory (Yang et al., 2017) (shown in Fig. 1). For example, Xu et al. (2014) proposed that the economic factor will exacerbate carbon emission since energy consumption is the foundation of economic development. However, by testing CKC theory, Andreoni and Levinson (2001) opined that a turning point exists presenting the relationship between carbon emission and GDP per capita, because of i.e. agglomeration effect, internalized externalities and the preference for environmental quality.

The results from this research echo these two mainstream

**Fig. 1.** The illustration of the CKC theory.

points. In Model 8, the significant coefficient of GDP per capita is “1.84”, which indicates it positively influences the generation of carbon emission. Obviously, this conclusion is in line with the view that the carbon emission continuously increases with GDP per capita. The CKC hypothesis can also explain the result. As pronounced by Chairman Xi Jinping at Paris conference 2015, China will reach the peak of carbon emission in 2030, indicating China hasn't reached the turning point now (Xinhua Website, 2017). The real GDP per capita thus contributes to carbon emission.

Notably, this is the major KIF for driving carbon emission in this research with comparing the coefficient with other factors. This results are also in line with previous studies conclusions (Wang et al., 2012). The real GDP per capita is the main driving factor for carbon emission due to the dramatically increase of per capita GDP brought the substantial increase of individual income, which in turn pushed the greater demand for energy products. The statistics are clear to support this.

As shown in Fig. 2, the real GDP has dramatically increased 3.9 times from 1995 to 2014, leading to the income increase by 2.6 times and energy consumption increase by 2.2 times. Zhang and Da (2015) and Shen et al. (2017a) stated that the economic development pattern in China is extensive, which only depends on adding the input of production material such as labor and scale investment to add the product, leads to the increment of the carbon emission. Therefore, Chinese governments should turn the economic development pattern from extensive into intensive, and achieve the decoupling relationship between economic development and carbon emission.

5.2. The urbanization rate

The urbanization rate factor is also a frequently selected

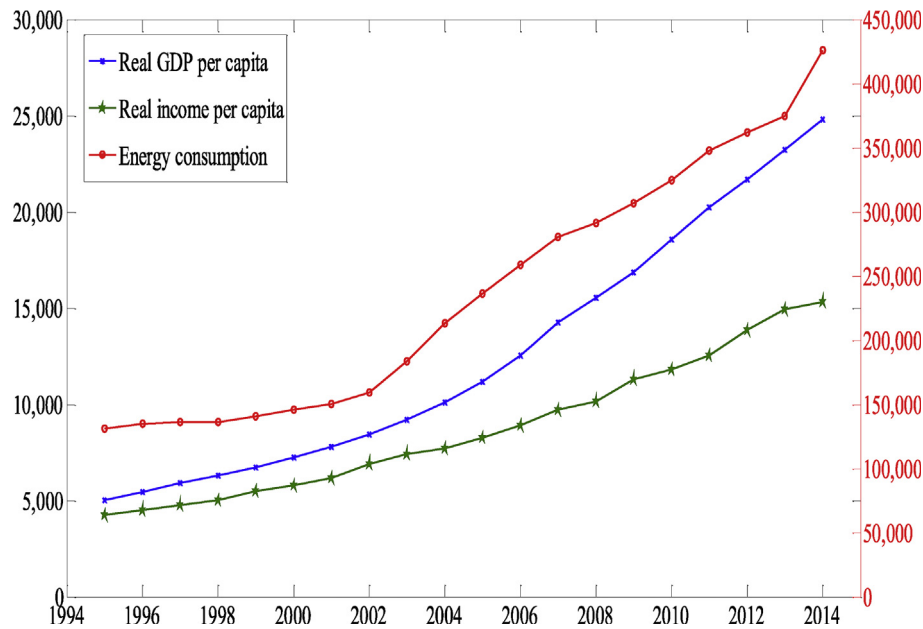


Fig. 2. The dynamic trends of three factors.

indicator by more than half of the studies in Table 1. However, there has been no agreement with its impact on carbon emission and there are three different mainstreams. Firstly, the urbanization can intensify the carbon emission (Li et al., 2011). Secondly, the urbanization can contribute to CER (Sharma, 2011). Thirdly, the inverted U-shaped relationship exists amidst carbon emission and urbanization process (Martínez-Zarzoso and Maruotti, 2011). Wang et al. (2012) suggested that urbanization significantly increase the carbon emission because it can greatly influence the domestic energy consumption such as in building and transportation sector, which will increase the carbon emission. However, the research by Sharma (2011) proposed that the population growth will eventually expand across the landscape and reduce the carbon emission by leading to an increase of the awareness of environmental impacts. Similar with CKC theory, Martínez-Zarzoso and Maruotti, 2011 argued that urbanization is a good proxy for modernization and therefore environmental impact (carbon emission) should decrease with higher shares of urban population.

The results from this research also echo the last two mainstream views. In model 8, the significant coefficient of urbanization rate is “-1.735”, which indicates it is the positive factor for CER. The conclusion accords with the opinion that urbanization contributes to CER. The research by He et al. (2017), which indicates the turning point of the inverted U-shaped curve shows when the urbanization rate is 30%. The urbanization rate in China in 1995 is 30%, which indicates the urbanization process indeed has been contributing to the CER since then.

Urbanization is the major KIF inhibiting the carbon emission comparing with the coefficients of other factors in this study. This results are also in line with previous research (He et al., 2017). Urbanization has the great agglomeration and technique effect for effective economic development. For example, Dodman (2009) suggested that compared with rural areas, urban areas have more intensive construction activities and smaller average living space, and more widespread public transport systems and less private car use, which will reduce energy use efficiently. Kaika and Zervas (2013) suggested these inhibiting effects led by development give the opportunity of investing in information-based industry and

services as well as improving production techniques or adopting cleaner technology. Therefore, the Chinese government should continue to promote the sustainable urbanization process to enlarge its positive effect on CER.

5.3. The ratio of tertiary to secondary industry

The ratio of tertiary to secondary industry represents the industrial structure. There is an agreement that the ratio of tertiary and secondary industry is a factor stimulating CER. Mi et al. (2015) and Xu et al. (2014) suggested that the secondary industries, i.e., electric power sector, and petroleum and natural gas exploitation industry, are energy and carbon intensive as they consume the greatest proportion of energy. However, the average energy and carbon intensity of tertiary industries (e.g., tourist and financial industry) are both less than those of secondary industries.

The results echo with these studies. In Model 8, the significant coefficient of the ratio of tertiary and secondary industry is “-0.654”, which indicates it is a positive factor for CER.

As shown in Fig. 3 (World Bank, 2015), the ratio of the secondary industry has slightly declined during the study period, nevertheless, the ratio of tertiary industry has increased, which leads to large increment of the ratio of tertiary to secondary industry. The average world ratio is 2.5, and France and UK's are both 4.0. In China, the ratio is only 1.1, which is much less than the average level of the world and the developed countries. Therefore, it is imperative for governors continue to upgrade the energy efficiency of industrial structure by enlarging the ratio of the tertiary industry.

5.4. The ratio of renewable energy

Renewable energy comes from five main low carbon sources: hydro-electric power, geothermal, solar, wind and biomass such as wood, wastes and biofuels (Zoundi, 2016). There is a strong agreement among researchers that renewable energy can stimulate CER. For example, Gullberg et al. (2014) defined the renewable energy as a kind of low carbon energy since it carries the lower carbon emission factors, which has a positive effect for CER. The

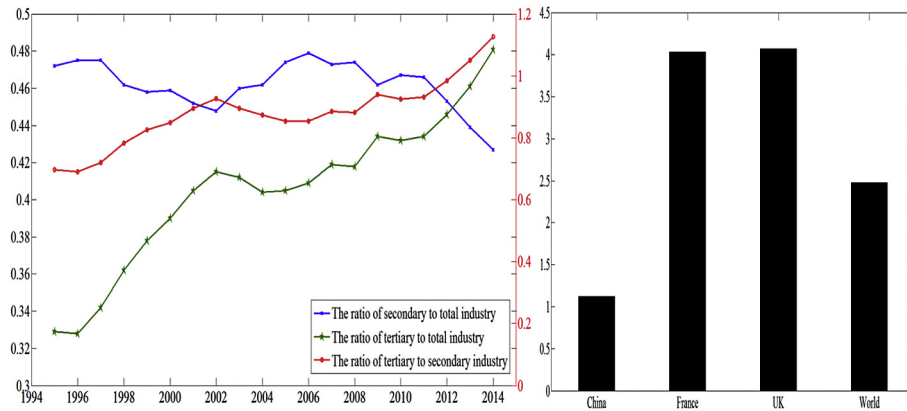


Fig. 3. The trends of the three factors.

report by Adib et al. (2015) stated that renewable energy technologies are effective mechanism for achieving carbon emission reduction goals. Zoundi (2016) concluded that overall estimations strongly reveal that renewable energy, coupled with an increasing long-run effect, remains an efficient substitute for the conventional fossil-fuelled energy. These results can also be proved from this research, as shown in Model 8, the significant coefficient the ratio of renewable energy consumption is “-0.342”, which indicates this factor has the positive effect for CER in China. However, this CER impact only occurs when the governments continuously improved the ratio of renewable energy.

As shown in Fig. 4 (World Bank, 2015), the ratio of the renewable energy is declining from approximately 30% to 15% during the study period (1995–2014). In other words, the ratio of fossil fuels such as coal has been dramatically increasing, which indicates this trend will induce more carbon emission rather than contributing the CER. The ratio of renewable energy is far lower than that of some other developed countries such as Iceland, Finland and Norway. Zhang and Lin (2012) explained that the relative low utilization of renewable energy in China is due to the rapid industrialization development, which highly depends on the fossil energies such as coal and oil. However, this utilization is still lower when compared with other rapidly developing countries such as Brazil and India. The expenditure on the renewable energy in China only accounts for less than 0.005% of the total expense (Statistics Database of Economic and Social Development of China (SDESDC), 2015). Coal, the most important carbon emission factor and the foundation of China's economic growth, dominates the present energy

consumption, accounting for 64.0% of total energy consumption in 2015 (Tang et al., 2016). China had produced 60% of the world's solar photovoltaic cells in 2014, yet less than 5% were installed domestically, and manufactured half of the wind-power capacity, but only one-third applied in the country (Liu, 2015). Therefore, the Chinese government should slash the reliance on coal, and enlarge the investment in research of renewable energy technologies and the promotion of renewable energy (Li et al., 2017).

5.5. The fixed assets investment

There are few opinions on the impact of this factor fixed assets investment on carbon emission. The fixed investment will induce the carbon emission, due to the investment will enlarge the transport, construction and manufacturing sector, which is considered as a contributor for increasing carbon emission (Ma et al., 2017c). However, different from previous studies, from this research, in Model 8, the coefficient of this factor is “-0.286”, suggesting a positive effect for CER. This may be due to the fact that with the urbanization process, considered as agglomeration and technique effect, the fixed investment increased which will upgrade the production craft and contribute to low-carbon development. Most of the fixed investment are inputted into the urban construction, which leads to the ongoing industrial restructuring, and is thus concluded as the contributor for CER (Zhang and Xu, 2017). Low-carbon city development has been long as the target of the Chinese government, which has required for the low-carbon building and transport sector (Shen et al., 2017b). For example, with

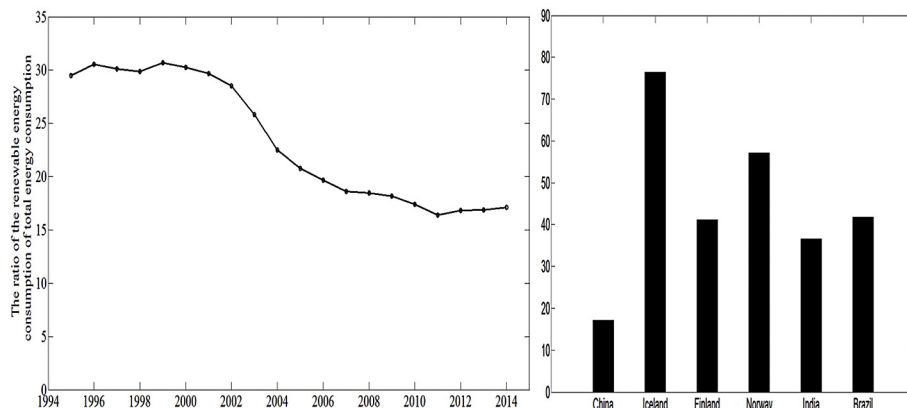


Fig. 4. The trend of the ratio of renewable energy.

green building development appreciated as an energy-efficiency and low-carbon approach, Chinese government has promoted strategies such as green procurement, green construction and green reformation (Ji et al., 2016) and invested more than 15 billions Yuan each year for promoting the green building development, contributing to 180 million squares' green area (Ministry of Housing and Urban-Rural Development of the People's Republic of China (MOHURD), 2007). However, the investment on the low-carbon city is still at relative low level, thereby, it is suggested the governments draw more attentions and enlarge the fixed assets investment on low-carbon city development.

5.6. Policy implications

According to the identified KIFs, this study raises some suggestions for the government to implement CER. As the real GDP per capita largely contributes to carbon emission, the government should target on developing the low-carbon economy, and achieving the decoupling between economic and carbon emission. For achieving this, it is necessary for the government to turn the current extensive economic pattern (i.e. economic increment from scale effect) to an intensive pattern (i.e. economic increment from technological effect). The strategies can be as follows: 1) promoting the emission trading system in China, where the volume of transactions of carbon emission in the system in 2013 is only 14 million tons, accounting for less than 0.5% of the total national emission; 2) improving the carbon tax especially on high-carbon sectors such as building, manufacturing and transportation sectors; 3) adding the CER target as a criterion to each province to evaluate the political performance rather than only with economic increment target; 4) more effectively implement economic incentives, such as reducing the difficulties for low-carbon firms to take out loans.

As urbanization rate is the major inhibitor of carbon emission, it is suggested to improve the effectiveness of promoting the urbanization process for CER. The Chinese government has implemented a series of strategies, such as the new-type or sustainable urbanization strategy, different from the traditional urbanization type, both pursuing the economic development as well as environmental protection. The effective actions should be maintained and encouraged to enlarge the positive effect of urbanization on CER. As the ratio of tertiary to secondary industry is an inhibitor to carbon emission, the government should adjust the industrial structure, especially encouraging the development of low-carbon tertiary industries, e.g., tourisms, financial and wholesale and retail sectors. It is also necessary to strictly control the emission of secondary industries (e.g., power, manufacturing and construction sector), promote upgrading the energy efficiency of these sectors, and eliminate the laggard output capacity, consisting recycling production chain. The application of innovative concepts and technologies, such as eco-design, cleaner production, energy audit and green construction should be promoted and shared among industries with the development of globalization. The ratio of renewable energy is also an important inhibitor on carbon emission, so it is necessary to adjust the energy structure particularly promoting the utilization of low-carbon energy such as solar, wind and biomass. China should rely less on coal by strictly controlling the increasing scale of coal-intensive sectors such as electric power and heating sector specifically in north of China. As the fixed assets investment is also an inhibitor to carbon emission, the government should increase it, particularly on the construction of low-carbon city program focusing on urban industrial symbiosis, green building including residential and commercial building, low-carbon transportation such as electro and hybrid car, and green infrastructure such as green belts and parks.

6. Conclusion

This study identified the KIFs on carbon emission in China from 43 PIFs selected through a comprehensive literature review. Finally, five KIFs are identified: the real GDP per capita, urbanization rate, ratio of tertiary to secondary industry, ratio of renewable energy, and fixed assets investment. Among them, GDP per capita most contributes to carbon emission, while urbanization rate is the top inhibitor. The identified KIFs in this study are believed as the credible and valuable reference for the governments to tailor policies to guide the domestic cleaner production and sustainable development for effective reducing carbon emission in China. For example, the governments should implement the carbon tax policy and establish the emission trading systems especially on the high carbon emission sectors, such as building, manufacturing and transportation.

This study has its limitations. This paper only identified the KIFs of carbon emission from a largely expanded pool of PIFs in China, as the top carbon emitter in the world. However, as climate change is a global issue, every country has the responsibility to mitigate carbon emission. Future studies are suggested to identify the KIFs in other countries using the expanded pool of PIFs for reducing global carbon emission.

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